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Productivity and Household Welfare Impact of Technology Adoption: Micro-Level Evidence from Rural Ethiopia*

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Abstract

This study evaluates the potential impact of improved agricultural technologies on smallholders' crop productivity and welfare. We use household-level data from Ethiopian Rural Household Survey collected by IFPRI in 1989-2009. The survey covers around 1500 rural households drawn from four regions and 15 rural villages. Endogenous treatment effect model is employed to account for the selection bias on households' technology adoption decision. The study employs both single and multi-level treatment effect approaches which is unique and represents a departure from previous impact evaluation studies which relied on single treatment effects. Results of the analysis indicate that there is positive and significant effect of improved technology adoption on the rural households' crop productivity and welfare in Ethiopia. Key factors for crop productivity and household welfare in the rural farm households are educational level, farm size, credit access, labor use, an extension program, expenditure for modern input and asset holding. While large household size negatively affects the welfare of households. For improving productivity, food security and welfare of smallholder farmers, policy priority should be an investment in research and development on major cereal crops adapted to local agroecological condition.

JEL Classification: D24, I31, Q18

Key words: Agricultural intensification, impacts, productivity, welfare, endogenous treatment effect model

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1 Introduction

There is a widely agreed belief that improved agricultural technologies are crucial for pro-poor development. Technological improvement holds a promise to stimulate the transition from low productivity subsistence agriculture to a high productivity and to enhance the expected linkage between sectors (Trigo and Cap, 2004). In many parts of the developing world, increasing agricultural productivity through the use of improved agricultural technologies is an important component of a strategy to increase income, reduce hunger, and to contribute to other measure of welfare (Owens et al., 2003). Agricultural productivity is essential to meet the increasing food demand of the growing population (World Bank, 2007). Thus, productivity growth in agriculture is not possible without yield increasing technologies such as high yielding varieties (HYVs) and inorganic fertilizers (Kassie et al., 2011).

Increasing productivity in agriculture depends on adopting production enhancing technologies and the innovativeness of actors in the sector, particularly farmers. Because of farmers capacity and actors along the agricultural value chain innovates production activity depends on the availability of production technologies (Akudugu et al., 2012). Therefore, improved agricultural technologies are important for productivity growth, reduce poverty, and meet food demands. According to DFID (2003), a 1 percent increase in agricultural productivity is estimated to reduce the percentage of poor people by 0.6 to 2 percent. There is no other economic activity that generates the same benefit for the poor. De Janvry and Sadoulet (2002a) argue that poor farmers could benefit from technology adoption by increasing production for home consumption and increasing gross revenue from crop sale.

Ensuring food security and reducing poverty in SSA can be realized by enhancing the productivity in agriculture that can be achieved through adoption of agricultural technologies or expansion of arable land. The latter option is less viable for spatial or environmental reasons. For instance, Hossain (1989) emphasized that agricultural growth will more depend on yield-increasing technological change since area expansion and irrigation have already become a minimal source of growth at a world scale. Jayne et al. (2003) also show that average per capita arable land has been declining in SSA over the last 40 years. Similarly, Degefa and Nega (2000) reported declining average land holding in Ethiopia. A viable option that remains is adoption of yield enhancing agricultural technologies. Most of agricultural productivity growth in the 1980s came from crop genetic improvement and new varieties development in Asia (Evenson, 2002).

For instance, in SSA, the Sasakawa-Global 2000 (SG-2000) project that is involved in food crop production technology transfer also supports farmers' crop production (Borlaug, 2000). The project, working with national agricultural extension services, successfully helped smallholders' to grow more than half a million Production Test Plot (PTPs) ranging in size from 1,000 to 5,000 square meters. The main concern of PTP is demonstrating improved technology for basic food crops such as wheat, maize, sorghum, cassava, rice, and grain legumes. The PTP yields are two-to-three times higher than the control plots employing the farmers' traditional methods (Borlaug, 2000).

About 82 percent of the Ethiopian population is living in rural areas and engaged in farming for their livelihood (World Bank, 2014). The high population growth and little application of improved production technologies resulted in declining per capita food consumption, escalating food deficit and deteriorating nutritional values (Borlaug, 2000). Ethiopia covers an area of 3, 498, 50 sq.km or 34.98 percent of agricultural land, of which 13, 948, 000 hectare or 13.95 percent are arable land. According to the 2014 World Development Indicators report, the arable agricultural land per rural person is 0.192 hectare and the average family size of the rural household is 5.1 (CSA, 2012). From these figures, the average land holding of farmers per household is 0.979 hectare. This indicates that farmers have fragmented land holding even if the major share of income of the rural households depends on agriculture. Improved agricultural technology adoption is quite vital to respond to food insecurity and poverty problems by improving productivity, income, and livelihood of farmers.

While Green Revolution had a major impact in Asia and Latin American countries in boosting agricultural productivity, the progress of adoption of agricultural technology and innovations in Sub-Saharan Africa has not been encouraging (Toborn, 2011). Agricultural innovations include new knowledge or technology related to primary production and commercialization that affect productivity, competitiveness and livelihood of farmers. Borlaug (2000) argued that although agriculture provides the livelihood to 70-85 percent of the people in most SSA countries, agricultural and rural development has been given low priority. Yet, continuing low agricultural productivity has contributed to persistence of poverty in agriculture-based countries especially in SSA (Christiaensen and Demery, 2007; Morris et al., 2007). Akudugu et al. (2012) also reported low adoption of modern agricultural production technology among Ghanaian farmers as one of the main reasons for low agricultural productivity. Although the positive impact of modern agricultural inputs on productivity growth is exhibited in the developing countries, in SSA adoption of the existing yield increasing technologies and skills is by far low (World Bank, 2007).

Basically the economy of Ethiopia is agrarian. The agricultural sector contributes for 46 percent of GDP, over 83.9 percent of export, and nearly 80 percent of employment (CSA, 2013). Besides, the major share of income of the rural households comes from agriculture. Governmental and non-governmental organizations have been committing huge resources for technology development and promotion of new and improved technologies in the country. For instance, the government has been increasing expenditure on agricultural extension, agricultural research, fertilizer and seed in the last couple of decades (Ayele and Paulos, 2008). Alene and Coulibaly (2009) also reported that doubling agricultural research expenditure per hectare in Africa can increase agricultural productivity by about 38 percent. Nevertheless, prior studies reveal that there is limited adoption of agricultural technologies by farmers (Akudugu et al., 2012). For instance, according to CSA (2013), improved seed use by farmers in Ethiopia has covered less than 5 percent of the cropped area. At national level, the proportion of inorganic fertilizer application is also around 46 percent (CSA, 2013).

The growth and innovation in Ethiopian agricultural sector is fairly weak by any standard (Spielman et al., 2011). As compared to South and East Asian countries (for example, China, 5706 kg/ha and India, 2883 kg/ha), productivity per hectare in Ethiopia is low (1761 kg/ha) (World Bank, 2012). This partly indicates the low adoption of productivity enhancing agricultural technologies. There has been also limited effort to quantify the impact of technology adoption on smallholder farm household performance. Indeed, there are few comprehensive technology adoption studies in Ethiopia, but they focus on conservation technologies (Kassie and Holden, 2006; Kassie et al., 2008; Hagos et al., 2006, 2008; Gebremedhin et al., 1999).

Previous studies on technology adoption determinants implicitly assume that the impact of agricultural technologies under consideration is beneficial in terms of enhancing productivity and welfare. However, the empirical evidence on the impact of technology adoption on productivity and welfare is mixed. De Janvry and Sadoulet (2002b) found positive direct and indirect effects of technology use on productivity and welfare in developing countries. Similarly, Kijima et al. (2008) found New Rice varieties for Africa (NERICA) to have poverty lessening impact in Uganda. Hossain et al. (2003) reported that adoption of a high-yield variety of rice has a positive effect only for the richer households, but had a negative effect on the poor. Gabre-Madhin and Haggblade (2004) show adoption of new highly yielding maize varieties to be faster among large commercial farmers than smallholders in Kenya. Bourdillon et al. (2003) observed that adoption of a high-yield variety of maize increases the crop incomes of adopters only modestly in Zimbabwe. Therefore, to contribute to the debate regarding the nature and multiple impacts of improved technologies, this study examines the differential impact of improved agricultural technology adoption on rural households by looking at the productivity impacts which ultimately translates into the welfare of households.

Using household level data from Ethiopian Rural Household Survey (ERHS), we measured productivity as value of all crops produced, and converted to a per hectare basis. Real per capita consumption expenditure is used as an indicator for welfare. The study follows both single and multi-level treatment effect approaches. This represents a departure from previous impact evaluation studies which tried to measure such impacts through single treatment effects. Endogenous treatment effect and sample selection models are employed to control for the effect of both observed and unobservable factors on technology adoption and the outcomes. Besides, a propensity-score matching method is also implemented. The results from the three approaches are comparable and show a positively significant effect of improved agricultural technologies on crop productivity and household welfare in Ethiopia. Thus, the analysis provides empirical evidence on the strong correlation between agricultural technology adoption and smallholders' crop productivity which ultimately translates into household welfare.

The rest of the paper is organized as follows. Section 2 provides review of empirical adoption literature. Description of the data and descriptive statistics of main variables are presented in section 3. The econometric model is presented in section 4. The results are presented and discussed in section 5. The last section concludes the paper.

2 Adoption Literature

Extensive literature demonstrates the benefit of agricultural technologies through a greater availability of food and lowering food prices (Alston et al., 1995). Studies such as Pinstrup-Andersen and Hazell (1985), Ahluwalia (1985) and Blyn (1983) show both the direct and indirect benefits of technological advancement on reducing poverty. Schultz (1980) also claims that in many low-income countries agriculture has the potential capacity for producing enough food for the growing population; thus the opportunity of increasing income and welfare of the poor might be through improved agricultural technologies. De Janvry and Sadoulet (2002a) argue that modern agricultural technologies affect poverty directly in Africa; indirectly through employment effect in Asia and through linkage effect in the rest of the economy in Latin American countries. There is also a positive direct and indirect welfare effect of technology use as explained by Simtowe et al. (2012). Similarly, the possible benefits through growth linkages with the rural non-farm economy have been pointed out by Bell et al. (1982), Haggblade and Hazell (1989) and Mellor and Johnston (1984).

Another dimension of technological change on technology adopters is through the changes in relative output prices. With the expansion of output through technological change in the face of relatively inelastic demand, the significant drop in output prices that results not only adverse income consequences for technology adopters but threatens the very process of sustained technological advance itself. For instance, Kuma (2002) observed the challenges of high-yielding variety use on output price. He claims that although the use of HYVs increases in grain production in Ethiopia, other developmental challenge of the fall down of grain price below the average level especially at the primary market will reduce producers' use of HYVs. Despite the fact that there is an increase in production at national level in the country, these could not overcome the food insecurity problem of the large population of the country (Kuma, 2002). This leads to the paradox of food abundance in the market with food insecurity at household level. Since the importance of agricultural technologies on production growth has been broadly accepted, their distributional consequences of inputs and outputs are threat to the development of agricultural technologies.

Various empirical adoption literature focused on the effect of farm size for new agricultural technology adoption (Boahene et al., 1999; Baidu-Forson, 1999; Doss and Morris, 2000; Daku, 2002). Farm size is an important factor which affects farmers' decision to adopt technology. Among others, Abara and Singh (1993), Kasenge (1998) and Fernandez-Cornejo (1998) found a positive relationship between farm size and technology adoption. They argue that for farmers having fragmented land holding, fixed costs become major constraints for agricultural technology adoption. Akudugu et al. (2012) point out that the rate of technology adoption is different for small and large scale farms with some technology.

On the contrary, Harper et al. (1990), Yaron et al. (1992) and Von Braun (1995) argue that farm size has a negative relationship with technology adoption. Pingali (1997) indicated that scarcity of land and water can be compensated by scientific knowledge and farmers' management. De Janvry and Sadoulet (2002a) also showed that technology adoption on crop production affect poor farmers who adopt the technological innovation. Earlier studies by Feder et al. (1985), Parthasarathy and Prasad (1978) and Ruttan (1977) reported that adoption of improved technologies such as HYVs exceptionally rapid in places where they are technically and economically superior to local varieties. Ruttan (1977) also claims use of new HYVs of grains is not constrained by farm size and tenure. Neither farm size nor tenure has been an important source of differential growth in productivity, but small farmers and tenants tended to lag behind large farmers in the early years following the introduction of new HYV. He claims that within a relatively few years after the introduction of new high yielding varieties, these lags in adoption rate due to farm size have typically disappeared. Parthasarathy and Prasad (1978) also reported the same. Initially use of HYV and some modern variable inputs tend to lag behind, but eventually small farmers catch-up later.

Beside farm size, availability of labor and human capital such as skills determines adoption of improved agricultural technologies. Minten and Barrett (2008) argue that lower illiteracy levels are generally associated with significantly higher adoption rate. In terms of creating awareness on improved agricultural inputs, (Owens et al., 2003) found that extension advice increase farm value of production by 15 percent. Asfaw et al. (2010) also shows the role of extension program in diffusing improved agricultural inputs. Feder and Umali (1993) and Feder et al. (1985) found human capital, labor availability and access to credit are the most important factors in influencing farmers' decision of technology adoption in developing countries. Therefore, due to farmers' heterogeneity behavior, their decision-making ability in technology adoption could be influenced by socioeconomic, institutional and other factors.

3 Dataset and Descriptive Statistics

3.1 The dataset

This study used data from Ethiopian Rural Household Survey (ERHS)[1] collected by International Food Policy Research Institute (IFPRI). The survey is a rich panel dataset covering about 1500 households from fifteen rural villages selected from four regions conducted from 1989-2009. This study used the recent two rounds of the 1999 and 2009 data to avoid the problem of missing observations. The two rounds have detailed information on agricultural production, consumption, and improved agricultural technologies. The survey covers the major cereal crops grown by rural households which is the focus of this research (Wheat, Maize, Teff, Sorghum, and Barley). Besides, more than 70 percent of the cultivated land is used for cereal crop production in Ethiopia (Yu et al., 2011). Even though the survey generated data from both agricultural season which is *Belg* and *Meher* seasons, we abstract from including the Belg season data for two reasons. One, the main rainy season in the country is *Meher* season and those major crops were grown in this rainy season which runs from June-September. Two, we reduce the noise of the data by excluding the *Belg* season. This is because agricultural production system depends on the productivity of the area, intensity of rain, and input usages which are different in a small shower of *Belg* season which runs from February-May (Seifu, 2004).

[1] Among the nine regional state of Ethiopia, ERHS covers four regions: region one (Tigray), region three (Amahra), region four (Oromia), and region seven (SNNPR).

Table 1: Summary statistics

Variables definition	Mean	Std. Dev.	Min	Max
Value of production in *Birr*	6210.5	8359.34	1.867	95575
Real PC consumption Expenditure in *Birr*	79.56	69.05	3.28	1018.3
Improved seed adopt (=1 if adopt, 0 otherwise)	0.18	0.38	0	1
Inorganic fertilizer adopt (=1 if adopt, 0 otherwise)	0.63	0.48	0	1
Improved seed and inorganic fertilizer (=1 if adopt both)	0.31	0.46	0	1
Gender of household head (=1 if Male, 0 otherwise)	0.79	0.40	0	1
Age of household head (years)	50.88	15.12	14	100
Marital status1 (married- reference= 1 if yes)	0.74	0.43	0	1
Marital status2 (never married=1 if yes)	0.02	0.15	0	1
Marital status3 (divorced/separated=1 if yes)	0.05	0.22	0	1
Marital status4 (widowed=1 if yes)	0.17	0.38	0	1
Educational level1 (illiterate- reference= 1 if yes)	0.51	0.49	0	1
Educational level2 (read and write=1 if yes)	0.12	0.32	0	1
Educational level3 (primary schooling= 1 if yes)	0.19	0.39	0	1
Educational level4 (secondary schooling= 1 if yes)	0.17	0.37	0	1
Household size (number of people per household)	5.89	2.58	1	17
Credit taken (=1 if yes, 0 otherwise)	0.58	0.49	0	1
Credit taken in *Birr*	429.63	889.92	0	12000
Total off/non-farm income in *Birr*	1193.55	5162.61	0	180000
Farm size cultivated in hectare	1.21	1.15	0	16.25
Type of land1 (fertile/Lem-reference)	0.52	0.49	0	1
Type of land2 (less- fertile/Lem-Teuf)	0.35	0.47	0	1
Type of land3 (not-fertile/(Teuf)	0.11	0.32	0	1
Slope of land1 (flatter/Medda- reference)	0.79	0.40	0	1
Slope of land2 (less-steep/Dagathama)	0.18	0.38	0	1
Slope of land3 (steeper/Geddel)	0.02	0.14	0	1
Labor use (working days)	59.27	77.26	0	885
Irrigation use (=1 if farmer used irrigation, 0 otherwise)	0.11	0.32	0	1
Soil conservation practice (=1 if yes, 0 otherwise)	0.46	0.45	0	1
Extension program participation(=1 if yes, 0 otherwise)	0.39	0.48	0	1
Livestock ownership (Tropical Livestock Unit)	4.81	4.96	0	46
Oxen (total number of oxen)	1.28	1.26	0	11
Tigray (region 1)	0.07	0.26	0	1
Amhara (region 3)	0.33	0.47	0	1
Oromya (region 4- reference)	0.39	0.48	0	1
SNNPR (region 7)	0.18	0.39	0	1
Year (=1 if survey year 1999, 0 otherwise)	0.46	0.49	0	1

3.2 Descriptive statistics

The socioeconomic, demographic, institutional factors, and resource endowments that are expected to influence the adoption of improved agricultural technologies and the outcomes (productivity and welfare) are included in the analysis. The descriptive statistics for these variables are presented in Table 2.

The proportions of male headed household are about 89 percent and 71 percent for adopters and non-adopters, respectively. The majority of adopters were married (85 percent) compared to non-adopters (67.8 percent). Households adopting improved technologies are headed by younger (48 years) heads than non-adopter households (51 years). They are also more educated farmers; perhaps this is why these households are more receptive to new ideas and innovation. The illiteracy rate among non-adopters is found to be higher (61.2 percent) than adopters (43.2 percent). The average household size for technology user households is seven whereas non-users have on average five members. This may support the idea that adopting labor intensive technologies such as HYV and inorganic fertilizer may depend on the availability of labor. The average farm size cultivated by technology adopters was 1.6 hectare which is relatively higher than for non-adopters (0.8 hectare). About 68 percent of technology adopters reported that their plots are fertile, whereas only 37 percent of the non-adopters have fertile land. This may be because adopters maintain the fertility of their farm by applying improved inputs such as inorganic fertilizer.

Technology adopters (86.9 percent) mainly have flatter plots than non-adopters (71 percent). However, perhaps the nature of the land may differ from farmer to farmer in terms of steepness, but some farm households practice soil conservation measure such as terracing in order to reduce soil erosion and degradation that may result from steepness of farm land. Technology user with the less-steep and steeper land found lower (12.5 percent and 0.61 percent, respectively) compared to non-users (24.24 percent and 4.62 percent, respectively), see Table 2. In the adopters' category, farmers who practice soil conservation measure are 37.6 percent where as non-adopters are 55.7 percent.

The use of mechanization such as irrigation technology seems lower in Ethiopia. Only 14.5 percent of agricultural technology users grow cereal crops through irrigation and the figure for non-users is 10.5 percent. This indicates that crop production is dominated by rain-fed agricultural production system. Livestock are important assets kept by rural households for both traction power and generating income. Technology adopters have an average of six livestock measured by Tropical Livestock Units (TLUs),[2] whereas non-adopters have three TLUs. The average number of oxen owned is two and one for adopters and non-adopters, respectively. Besides agricultural activity, farm households participate in non-farm income activities. On average, technology users generated 1,943 Ethiopian *Birr*[3]

[2]Tropical Livestock Unit (TLU) is the standard method of quantifying a wide range of different livestock type and size.

[3]*Birr* is a currency in Ethiopia

per year, whereas non-users earned 559 *Birr*. The sources of labor in the rural farm families are from their own household, through labor sharing with neighbor farmers, and through renting landless wage laborers. Measuring in working days, technology users practices 84 working days per year compared to non-users (nearly 41 working days).

Providing credit access in the form of cash or in kind is the government's strategy to support rural farm families. Around 71.6 percent of agricultural technology users have taken cash credit compared to 54.1 percent of non-users. On average adopters borrowed 816 *Birr*, while non-adopters received 272 *Birr*. The government also disseminates information about agricultural technologies and innovative practices through public agricultural extension program. The participation of technology users in the program is 62.4 percent compared to 28.3 percent of non-users. This indicates that farm households who participate in the program increase their adoption behavior. Farmers' who apply improved agricultural technologies have an average value of production amounting to 11,022 *Birr* per year compared to 2,850 *Birr* for non-users. In the adopters category, the average per capita consumption expenditure of farm households is 78 *Birr* per month and for non-adopters it is nearly 71 *Birr*. All the differences discussed above are statistically significant (see Table 2).

Table 2: Descriptive statistics

	HYVs			Fertilizer			Multiple		
Variables	Treated	Control		Treated	Control		Treated	Control	
	Mean (SD)	Mean (SD)	t/χ^2	Mean (SD)	Mean (SD)	t/χ^2	Mean (SD)	Mean (SD)	t/χ^2
Household demography									
Age of household head	48.54	51.3	3.24***	50.5	51.2	0.92	48.8	51.5	2.7***
	(13.30)	(15.55)		(15.1)	(15.4)		(13.4)	(15.5)	
Gender:									
Male	88.17	77.87	-4.58***	84.1	72.2	-6.69***	88.9	71.3	-6.4***
Female	11.83	22.13		15.8	27.8		11.1	28.7	
Educational level:									
Illiterate	44.13	53.34		46.27	60.44		43.2	61.2	
Read and write	6.53	14.02		12.09	13.37		6.4	13.97	
Primary school	26.37	17.02	-5.01***	22.18	13.5	-6.76***	27.0	12	-7.2***
Secondary school	22.96	15.61		19.47	12.7		23.4	11.89	
Marital status:									
Married	83.3	72.4	2.2**	80.0	68.8	3.0***	85.0	67.8	2.9***
Divorced or separated	3.1	7.4		3.5	3.0		1.5	9.37	
Widowed	13.37	17.31		14.95	19.95		13.17	19.58	
Never married	0.26	2.90		2.07	2.96		0.3	3.22	
Household size	6.5	5.74	-6.16***	6.3	5.2	-9.56***	6.8	5.2	-9.1***
	(2.54)	(2.53)		(2.54)	(2.47)		(2.7)	(2.4)	
Resource ownership									

Continued on next page...

Table 2 – continued

Farm size cultivated	1.53	1.16	-5.69***	1.4	0.8	-12.08***	1.6	0.8	-11.0***
	(1.42)	(1.05)		(1.2)	(0.8)		(1.4)	(0.8)	
Type of land:									
Fertile	67.6	48.3		58.9	39.2		67.8	37.1	
Less-fertile	28.7	37.6	7.7***	33.6	39.9	10.7***	28.9	40.9	10.6***
Non-fertile	3.7	14.2		7.4	20.9		3.3	21.9	
Slope of the land:									
Flatter	86.95	78.37		84.12	72.17		86.9	71.14	
Less-steeper	12.53	19.23	4.02***	15.07	23.57	7.41***	12.5	24.25	5.8***
Steeper	0.52	2.40		0.81	4.26		0.61	4.62	
Soil conservation practice	38.4	48.7	3.7***	42.25	54.83	5.7***	37.6	55.7	5.5***
Irrigation use	18.32	10.23	-4.52***	11.02	12.6	1.15	14.5	10.5	-1.8*
Livestock owned	6.1	4.6	-5.23***	5.74	3.32	-11.26***	6.3	3.2	-10.4***
	(5.77)	(4.74)		(5.37)	(3.68)		(5.9)	(3.6)	
Oxen owned	1.6	1.2	-4.76***	1.6	0.9	-12.37***	1.7	0.8	-9.7***
	(1.65)	(1.14)		(1.33)	(0.98)		(1.6)	(0.9)	
Labor use	79.4	55.6	-5.6***	70.6	41.3	-8.6***	83.7	40.7	-9.2***
	(84.2)	(74.9)		(82.45)	(62.7)		(85.6)	(62.4)	
Off-farm income	1943.6	950.4	-3.2***	1398.9	665.7	-2.9***	1943.2	558.6	-7.8***
	(3912.5)	(5308.9)		(6265.2)	(1549.7)		(3994.5)	(1226.7)	
Institutional variables									
Credit taken	71.5	55.3	-5.9***	60.0	55.2	-2.2**	71.6	54.1	-5.4***
Amount of credit (*Birr*)	789.4	326.7	-8.86***	475.3	301.7	-4.1***	816.7	272.06	-8.3***
	(1310.05)	(706.64)		(961.8)	(659.6)		(1339.4)	(598.1)	
Extension service	62.6	34.3	-10.6***	44.5	30.1	-6.3***	62.4	28.3	-11.2***

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Table 2 – continued

Dep. and treat. indicator									
Value of production	9897.24	5518.9	-9.5***	8331.3	2864.9	-15.3***	11022.3	2849.8	-15.0***
	(13438.6)	(6609.8)		(9849.4)	(2888.6)		(14130.8)	(2893.9)	
Real Pc consumption exp.	75.1	81.4	1.43	86.6	70.2	-5.1***	78.0	70.7	-1.7*
	(57.08)	(72.07)		(75.8)	(57.6)		(59.6)	(58.5)	
Amount of improved seed	55.8	0	-22.1***						
	(106.2)	(0)							
Amount of inorganic fertilizer				100.26	0	-25.9***			
				(108.9)	0				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Standard deviations in parentheses

Source: Author calculation using ERHS data 1999 and 2009.

The finding of our descriptive statistics indicates that agricultural technology adoption has a role in improving smallholders' crop productivity and welfare of households. However, comparing adopters and non-adopters performance might not be a causal interpretation, because these results are only based on observed mean differences in outcome of interest and may not be solely due to improved HYVs and inorganic fertilizer use, instead may be due to other factors such as differences in household wealth, and other related socioeconomic factors. Hence, we do not know whether the productivity and welfare performance of adopters is caused by technology use or not. Our interest is, to know if technology adoption increases productivity and welfare of households or if the positive effect we observe is because of for instance, wealthier households being able to adopt improved technologies and what the underling causality would be. To measure the true impact of technology adoption, it is necessary to take into account the fact that households who adopt HYVs and inorganic fertilizer might have achieved a higher level of productivity and welfare even if they had not adopted.

The main drawback of many adoption studies is that, they do not explicitly point out the causal effect of improved agricultural technologies adoption on farm household productivity and welfare, and they fail to establish an adequate counterfactual situation. To identify the true impact of improved technologies, it is important to look at the counterfactual situation and identify the true causal effect. Simple comparison between the performance of adopters and non-adopters may lead to misleading policy implications since there are many factors that influence the decisions of households towards technology adoption. This is an important methodological issue in evaluating the potential impact of HYVs and inorganic fertilizer on crop productivity and welfare of rural smallholder farmers. Moreover, methods are established to evaluate either to look at the effect of HYVs or inorganic fertilizer (one treatment indicator); however estimating multiple treatments may face methodological challenge. This is because there are some households adopting both technologies simultaneously. Hence, this study tried to tackle such challenge in the estimation. In the next section, the study first looks at farm households' level of adoption. Then, controlling for observed covariates, we econometrically estimate the impact of smallholder farmers' adoption of improved agricultural technologies on crop productivity and welfare of rural households.

3.3 Rate of technology adoption

The rate of adoption between the two promoted technologies of HYVs (i.e. adopting at least one of the five major cereal crops) and inorganic fertilizer varies across the years (see Table 3). Because of missing values for some of the regressors, 1,041 households are used rather than 1500 from 1999 data, and 1,114 from 2009 data. Out of 1,041 household, the size of HYVs users was only 104 households (9.99 percent). The number of HYVs users increased to 289 households (25.94 percent) in 2009. In the case of inorganic fertilizer, the size of user households was higher, which is 641 households (63.31 percent) than non-users that is 400 households (36.69 percent) in 1999. In 2009, the rate of inorganic fertilizer users slightly increased to 737 households (64.90 percent), and the rest are non-users. This indicates that farmers rate of inorganic fertilizer adoption is much better than the rate of HYVs adoption. This may be due to the better availability of inorganic fertilizer than HYVs. However, even though the dataset we used is not nationally representative, the descriptive statistics shows us there is improvement in HYVs adoption from 9.9 percent in 1999 to 25.9 percent in 2009. Yet, in both cases the percentage we found is higher than the national statistical average figure which is less than 5 percent (CSA, 2013).

According to Taffes et al. (2013), at national level the percentage of HYVs use in Ethiopia is 4.7 percent and around 46 percent of inorganic fertilizer. This indicates that HYV use is low, and the majority of farm households produce cereal crop through local seeds, and hence local seed remains the dominant system. Similarly, CSA (2013) reported that from the total cultivable area of 12.3 million hectare, about 9 million hectare is under cereals, however the application of improved seed is less than 5 percent of the total cultivated areas. This may be a lesson for technology development research institutions and distributing organizations about why farmers are lagged behind in the use of high-yielding varieties particularly in rural areas where there is food insecurity and poverty problems. Even though there are a diverse set of agro-ecological conditions, the application of HYVs is lower in the country. In line with this, Taffes et al. (2013) reported that Ethiopian yield levels are lower than the average yield in Least Developed Countries as defined by the United Nation.

Table 3: Adoption rate

Panel A: by year

	HYV			Fertilizer		
	Adopters	non-adopters	Total	Adopters	Non-adopters	Total
1999	104	937	1,041	641	400	1,041
2009	289	825	1,114	737	397	1,134
Total	393	1,762	2,155	1,041	1,131	2,172

Panel B: pooled data

HYV	Fertilizer		
	Adopters	Non-adopters	Total
Adopters	55	338	393
Non-adopters	735	1,025	1,760
Total	790	1,363	2,153

Source: Author calculation using ERHS data 1999 and 2009.

3.4 Households access to improved technologies

Although high quality seed is a product of research, trials, and manufacturing, the distribution of the right type of inputs of good quality on timely bases is the key for farmers especially in the rural areas. The seed sector in Ethiopia composed of both formal and informal components. The formal sector of public research organizations develops new varieties, an extension system introduces these varieties to rural farmers, and both public enterprises and private companies multiply the seed varieties. However, the role of private sectors is limited in Ethiopia, which has been largely privatized in many other developing countries. DFID (2008) explained in its report that private sector technology generation and distribution is of growing relevance to poverty reduction strategy, but it is probably unreasonable to place high expectations on vastly expanded formal public-private partnership.

Ethiopian Seed Enterprise (ESE) is a fully governmental owned parastatals body designed to undertake seed production, processing, and distribution.[4] However, previous studies show that the distribution system of key inputs such as HYVs and inorganic fertilizer is inflexible. Recently, Spielman et al. (2011) reported that in Ethiopia production and distribution of improved seed has been stagnant since about 2000. Besides the shortcoming in improved seed quality and timeliness of delivery have been longstanding issues in the country. According to DSA (2006), although official figure indicates that production of crop seeds by ESE improved over the last five years, the 2012/13 supply remained short of requirements and was fairly volatile, especially for those of major cereal crops. At the same time, DSA (2006) argued that more than 25 percent of farmers com-

[4] See Alemu et al. (2010) about the production and distribution system of improved seeds.

plained late delivery of inorganic fertilizer. Bonger et al. (2004) also show half of farmers noted that the fertilizer arrived after planting, 32 percent reported underweight bags, 25 percent indicated poor quality, and almost 40 percent reported that their planting was delayed by fertilizer problem. Hence, the timely availability of improved agricultural inputs is critical in the rain-fed agriculture production system, however, late delivery and application causes unprofitability for smallholders and resource-poor farmers, and delayed planting may incur even high costs.

Although there are some private companies involved in diffusing improved agricultural technologies, they are owned by regional government, and their shares are 24.91 and 24.04 percent, respectively. The share of Ministry of Agriculture (public organization) in distributing HYVs and inorganic fertilizer is 66.40 and 58.53 percent, respectively. The participation of private sectors is too small (0.79 and 3.31 percent, respectively). Farmers also access inputs from farmers group (4.74 and 12.74 percent, respectively), and the shares of others are 3.16 and 1.36 respectively (see Table 4).

Table 4: Source of improved technologies

Source	HYV	Inorganic fertilizer
Ministry of Agriculture	66.40	58.53
Private dealers owned by regional gov't	24.91	24.04
Farmer groups	4.74	12.74
Private trader	0.79	3.31
Others	3.16	1.36

Source: Author calculation using ERHS data 1999.

4 Empirical Analysis and Estimation Strategy

4.1 Impact evaluation techniques

Evaluating impact of improved agricultural technology adoption on productivity and household welfare using non-experimental data is challenging, since the counterfactuals are unobserved, that is we do not observe what would have happened had the farmer did not adopt technologies. This implies that we have problem of missing data to look at the counterfactual. Thus, we estimate the direct impact of improved technologies on crop productivity and welfare. Moreover, farmers may not be randomly assigned that they would self-select to adoption of technologies due to factors unobservable to the researcher. This is because, technology adoption is either voluntarily adopted or some technologies are targeted to a given group of farmers. For instance, more productive farmers could be those who adopt modern technologies; in this case, self-selectivity into technology adoption is the source of endogenity (Hausman, 1978).

From econometric viewpoint, evaluation of impact of technology adoption may be challenging due to endogeneity that would arise from self-selection bias. To address this problem, we adopt an endogenous treatment effect model. The endogenous treatment effect model is a linear potential outcome model that allows for a specific correlation between the unobservable that affect the treatment and the unobservable that affect the potential outcomes. The model estimates the average treatment effect (ATE), and other parameters of a linear regression augmented with an endogenous binary treatment variable. This model is a specific endogenous treatment effect model, it uses a linear model of the outcome variables (productivity and welfare) and a constrained normal distribution to model the deviation from the conditional independence assumption imposed by the estimator implemented in the treatment effect (adoption of technologies). In addition to the average treatment effect, the model can be used to estimate the average treatment effect on the treated (HYVs and inorganic fertilizer adoption) when the outcomes (productivity and welfare) may not be conditionally independent of the treatment.

After estimating the main model used for analysis (endogenous treatment effect model), two other models are used to check robustness of the result: Heckman two-step selection model, and Propensity-Score Matching (PSM). Heckman model estimates a binary treatment with heterogeneous response to treatment under observable and unobservable selection. This is because, the selection into treatment is not only governed by observables to the analyst factors, but also by unobservable. In this case the selection model known as Heckit model is particularly suitable, and reduces the bias in the estimates of the covariates and selection into treatment (Cerulli, 2012). The model estimates the average treatment effect (ATE), the average treatment effect on treated (ATET), and the average treatment effect on non-treated (ATENT), as well as the estimates of these parameters conditional on the observable covariates. When evaluating the two groups of households, treated and untreated, assuming that the two different and exclusive outcomes that household who adopt technology and the same households who did not adopt technology may respond differently both to specific observable covariates and to the treatment.

The second model we estimate is propensity-score matching. In the PSM model, once we control the observed factors which affect technology adoption, the conditional independence assumption allows us to rule out the potential unobserved characteristics in the propensity score. The assumption is that technology adoption is random and uncorrelated with crop productivity and households welfare. The PSM uses a treatment model to model the conditional probability that households adopt improved technologies with observed characteristics known as propensity-score, and the PSM matches on the estimated propensity score. The model identifies similar households based on observed covariates and ranks them towards technology adoption. The PSM uses an average of the outcome of similar households who adopt improved technology to impute the non-adopter potential outcome for each household. Thus, the average treatment effect (ATE) is computed by taking the average of the difference between the observed and potential outcome for each household.

After estimating the propensity score to capture the similarities of households, we match each household who adopt technology with the closest households who did not adopt technology based on observed similarities. Doing so, we used Nearest Neighboring Matching (NNM). The PSM matches on a single continuous variables and does not need correction bias, however nearest neighbor matching uses a bias correct term when matching on more than one continuous variable. The NNM identifies the closest pairs in the opposite technological status, and then it computes estimates of the technological effect as the average difference of productivity and welfare of each pair of matched households. With similar estimation procedure as NNM, the Kernel Based matching (KBM) is more flexible with regard to specification of propensity score; however, the matching household is identified as the weighted average of all households in the opposite technological status within a certain propensity score distance with weights inversely proportional to the distance.

4.2 Estimation procedure

Evaluating the impact of technology adoption on productivity and household welfare using ordinary least squares may lead to parametric biases due to the presence of omitted variables that are correlated with other covariates. This is because the decision of households towards technology use will not only be due to observed characteristics, but also unobservable factors which are not seen by the researcher, in this case OLS estimation will result in parametric bias. According to Barnow et al. (1980), the self-selection bias of the simple OLS estimator of the treatment effect is nonzero, and of a specific sign. Hence, endogenous treatment effect model is applied to take into account the endogeneity of households adoption decision. Wooldridge (2010) discusses the endogenous binary variable model as an endogenous treatment effect model. In this model Heckman (1976, 1978) brought this model into the modern literature; Maddala (1983) drives both the maximum likelihood and two-step estimators. Applying endogenous treatment effect model is a consistent approach in this estimation to address problem of the selection bias. Econometrically, the model can be specified as:

$$Y_j = \alpha + X_j\beta + \delta t_j + \epsilon_j \tag{1}$$

Where Y_j is the outcome variable of household productivity and welfare,[5] X_j are the covariates used to model the outcome variables, t_j is the treatment variable, β and δ are the parameters to be estimated, α and ϵ are the constant and disturbance terms, respectively. Thus, the binary treatment variable (t_j) is assumed

[5]We follow the same estimation procedure of household productivity and welfare in the endogenous treatment effect model.

to stem from an unobservable latent variable. The selection equation can be specified as:

$$t^* = \gamma z_j + u_i \tag{2}$$

$$t_j = \begin{cases} 1 & \text{if } t_j^* > 0, \text{ for adopters} \\ 0 \text{ , } otherwise, & \text{for non-adopters} \end{cases} \tag{3}$$

Where z_j is the covariates used to model treatment assignment (HYVs and inorganic fertilizer), γ is the parameter to be estimated, and u is a random disturbance associated with technology adoption. From equation (1) and (2), the error terms ϵ and u are the bivariate normal distribution with mean zero and covariance matrix:

$$Cov = \begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix} \tag{4}$$

Where σ^2 is the variance of disturbance term (ϵ) in the main outcome regression equation (1), the variance of the error term (u_i) in the selection or treatment equation (2) of technology adoption assumed to be one; which is $\delta^2 = 1$, and $\rho\sigma$ is the covariance of ϵ and u_i. The covariates X_j and z_j are uncorrelated to the error term, that means they are exogenous. Using maximum likelihood estimation technique, we estimate the endogenous treatment effect model. The maximum likelihood estimates provide us consistent and asymptotically efficient results. The likelihood function for this model discusses the standard method of reducing a bivariate normal to a function of a univariate normal and the correlation σ. The log likelihood function for equation (1) and (2) for household j is expressed as:

$$lnLj = \begin{cases} ln\Phi\left\{\frac{z_j\gamma+(y_j-x_j\beta-\delta)\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_j-x_j\beta-\delta}{\sigma}\right)^2 - ln(\sqrt{2\pi\sigma})t_j = 1 \\ ln\Phi\left\{\frac{-z_j\gamma-(y_j-x_j\beta)\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_j-x_j\beta}{\sigma}\right)^2 - ln(\sqrt{2\pi\sigma})t_j = 0 \end{cases}$$

Where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution. In the maximum likelihood estimation σ and ρ are not directly estimated, instead $ln\sigma$ and $atanh\rho$ are directly estimated. Thus, $atanh\rho = \frac{1}{2}ln(\frac{1+\rho}{1-\rho})$. The standard error of $\lambda = \rho\sigma$ is approximated though the delta method, which is given by: Var (λ) $\approx$ I Var $\{(atanh\rho ln\sigma)\}$ I'. Where I is the Jacobian of λ with respect to $atanh\rho$ and $ln\sigma$.

5 Estimation Result

This section discusses the findings of the econometric analysis. Using endogenous treatment effect model, the impact of technology adoption on productivity and household welfare are examined. The outcome variables productivity is measured in value of production in monetary terms at community level price. Household welfare is measured in real per capita consumption expenditure.

5.1 Productivity impact of technology adoption

While the use of innovative technologies in agriculture offers an opportunity for improving productivity and income of smallholders substantially, in most cases, adoption behavior differs between households due to socioeconomic, demographic, institutional factors, and geographical areas. Controlling for the endogeneity of technology adoption decision by farm households, the model results show that improved agricultural inputs positively contributed for smallholders' crop productivity. Specifically, HYVs adoption increases farm value of production by 7.37 percent for adopter households. Similarly, inorganic fertilizer use increases productivity by 6.32 percent. The effect is comparable in the multiple adoption of both HYVs and inorganic fertilizer (5.82 percent).

In this estimation, the average treatment effect on treated household (ATET) is the same as the average treatment effect (ATE). This implies that the average predicted outcome for the treatment group is similar to the average predicted outcome for the whole population. The estimated correlation coefficients between the two error terms in the main outcome regression (productivity) and treatment assignment (technology adoption) are -0.86, -0.56, and -0.76, respectively (see Table 5). This indicates that the unobservables that improve the observed crop productivity tend to occur with unobservables that affect households' technology adoption decision, suggesting that there is relationship between technology adoption and productivity. The likelihood ratio test result also shows statistically significant, and hence we can reject the null hypothesis of no correlation between technology adoption and crop productivity.

Table 5: Endogenous treatment effect estimation result

	HYV		Fertilizer		Multiple	
Vale of Production	Coeff.	Std. Err.	Coeff	Std. Err.	Coeff.	Std. Err.
Treatment indicator	7.378***	0.372	6.321***	0.561	5.824***	0.549
Gender of head	0.518	0.332	0.586	0.357	-0.115	0.463
Age of household head	0.016	0.047	-0.042	0.049	-0.032	0.064
Age square	-1.113	2.248	0.869	2.394	0.842	2.973
Educational level2	1.286***	0.502	0.749*	0.455	0.568	0.733
Educational level3	0.464	0.454	0.290	0.410	-0.330	0.588
Educational level4	0.905**	0.462	0.811*	0.423	1.130**	0.569
Household size	-0.035	0.054	-0.060	0.058	-0.001	0.079
Credit taken	-0.133	0.265	-0.100	0.283	-0.429	0.379
Off/non-farm income	0.001	0.001	0.001	0.002	0.002	0.006
Farm size cultivated	2.016***	0.197	1.630***	0.181	1.589***	0.299
Quality of land2	-0.257	0.286	-0.544*	0.305	0.390	0.413
Quality of land3	-0.637	0.461	-0.858*	0.477	-0.413	0.607
Slope of land2	-0.539	0.342	-0.798**	0.366	-0.494	0.442
Slope of land3	-0.652	1.298	-0.495	1.389	-0.545	1.493
Labor use	0.013***	0.002	0.012***	0.002	0.012***	0.003
Irrigation use	-0.634	0.391	-0.146	0.419	-1.310 ***	0.501
Soil conservation	0.069	0.291	0.518*	0.308	-0.584	0.410
Number of TLU owned	0.000	0.038	0.036	0.041	-0.047	0.058
Number of oxen owned	1.631***	0.181	1.273***	0.174	1.236***	0.267

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Table 5 – continued

Tigray	-2.299***	0.621	-1.847***	0.690	-2.625***	0.763
Amhara	-1.349***	0.346	-1.215***	0.368	-1.909***	0.535
SNNPR	-3.646***	0.384	-3.243***	0.404	-4.086***	0.565
Year	-0.041	0.031	0.86**	0.036	0.015	0.049
Constant	3.359	6.361	-3.460	6.797	-0.631	8.3200
Treatment indicator						
Expenditure for inputs	0.051***	0.004	0.074***	0.010	0.081***	0.008
Extension program	0.440***	0.067	-0.369***	0.084	0.248**	0.112
Age of household head	-0.009	0.003	-0.001	0.003	-0.009	0.005
Educational level2	-0.373	0.137	0.130	0.143	-0.136	0.227
Educational level3	-0.130	0.113	0.161	0.124	0.145	0.181
Educational level4	-0.111	0.113	-0.153	0.124	-0.149	0.180
Labor use	-0.001	0.000	-0.002	0.000	-0.001	0.001
Farm size	-0.175	0.050	0.146	0.056	-0.031	0.092
Number of oxen owned	-0.099	0.041	0.163	0.046	0.144	0.071
Constant	-0.232	0.178	0.618	0.188	0.062	0.291
athrho	-1.307	0.063	-0.662	0.074	-0.995	0.099
lnsigma	1.653	0.025	1.547	0.026	1.376	0.047
rho	-0.863	0.016	-0.579	0.049	-0.759	0.042
sigma	5.227	0.131	4.701	0.126	3.962	0.189
lambda	-4.514	0.174	-2.725	0.285	-3.010	0.284
Estimator:ml						
Log likelihood		-3790.3		-3869.3		-1276.1

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Table 5 – continued

Number of obs	1150	1158	400
Prob > chi2	0.000	0.000	0.000
LR test (rho=0):	$chi^2(1) = 167.9$	$chi^2(1) = 34.7$	$chi^2(1) = 53.9$

The major factors that significantly affect farmers' technology adoption and crop productivity are reported in Table 5 and 6. Educational level of the household head in the form of human capital formation exhibits higher impact to farmers new agricultural technology adoption. The positive correlation between education and technology adoption shows that educated farmers could have positive attitude towards innovative technologies. Similarly, Caswell et al. (2001) and Waller et al. (1998) found that education affects technology adoption positively by relating to years of formal schooling.

Especially for information intensive and management practices, education has greater role. Although farmers own and neighboring experience influence the adoption of new agricultural technologies, the imperfect knowledge about the management of new technologies is a barrier for adopting modern inputs (Foster and Rosenzweig, 1995). This indicates that modern technology use is associated with farmers' skill, and hence education indeed increases productivity. Producers with high level of knowledge adopt new technologies more rapidly than lower education and non-adopters are associated with uneducated farmers. This shows that the likelihood of new agricultural technology adoption is positively related to producer skills (Feder et al., 1985).

A positively significant effect of farm size on productivity outcome indicates that the probability of adopting new agricultural technologies correlates with the farm size. Fernandez-Cornejo (1998) and Abara and Singh (1993) reported similar findings. According to Kasenge (1998), large scale farmers are more inclined to adopt new technologies than small-scale farmers. However, this study is on small-scale agriculture on farm households producing crops on less than a hectare of land. Perhaps this might be a challenge for policy makers in promoting new technologies.

The type of farm land in terms of fertility significantly affect crop productivity in the case of inorganic fertilize adoption. Using fertile land as a reference, the less-fertile and non-fertile land also affects crop productivity. This indicates that farmers' practicing on a less-fertile and non-fertile farm land can be productive through the application of yield increasing technologies. In line with this, earlier study by Schultz (1980) shows with some local exceptions, the original soils of Europe were poor in quality, for instance, Finland were less productive to the neighboring western parts of the Soviet Union, but they are more productive today. Likewise, originally Japanese croplands were inferior, yet they are superior in productivity than northern India. This suggests that improved agricultural inputs increase yields even in the areas where productivity is low. Devereux and Sussex (2000) also indicated that the declining soil fertility due to intensive cultivation in Ethiopia makes crop production low, thus the limited application of yield-enhancing technologies exacerbate the food insecurity problem.

Classifying the slope of land into flatter, steep, and less-steep, flatter land type significantly affect productivity than steeper and less-steep. This is because the later two are exposed to soil erosion and degradation, suggesting that farmers need to use other soil conservation mechanism. Kassie et al. (2008) indicated that soil conservation measure makes the soil more productive even in low productive and rainfall areas by protecting the fertility and soil moisture. Soil conservation measures such as drainage ditches during extreme rainfall events in the place where there is higher rainfall areas help to protect soil runoff. Farm households who practice soil conservation measure significantly affect their crop productivity in the case of inorganic fertilizer adoption. This indicates that soil conservation technology is a complementary input with other agricultural technology like inorganic fertilizer.

The use of mechanization such as irrigation technology reduces the risk of spatial and temporary variation of rainfall; however, in this study smallholders' who use irrigation have lower crop productivity. Perhaps may be other factors related to irrigation technology such as lack of management of such technology may have affected productivity negatively. Similarly, Yu et al. (2011) found irrigation to be negatively related to fertilizer adoption in teff and wheat production in Ethiopia. They argued that farmers still view irrigation as a substitute for other inputs rather than as a complementary technology. Since irrigation plays a leading role in food production and nation development in different countries, farmers' active involvement in irrigation management, especially operation and maintenance of irrigation materials has been identified as a key requirement to attain productivity goals and the sustainability of irrigation (Jinapala et al., 2010). In the revisited green revolution study, Blyn (1983) reported that the higher water supply, and controlling time and volume of water is essential for crops production through irrigation in India.

As one of the important factors of production, labor use measured in working days is positively correlated with productivity. Similarly, Feder et al. (1985) reported that agricultural technology adoption increases seasonal labor demand. This is important in countries like Ethiopia where there is more surplus labor, especially in rural areas where the job market is limited. Assuming that HYVs and inorganic fertilizer are labor intensive technologies, it is expected that availability of labor may result in increasing the use of such technologies, implying that adoption of HYVs and inorganic fertilizer is a labor intensive technology. Parvan (2011) indicates that labor saving technologies will be adopted in areas where there is shortage of labor, but not labor surplus. Hicks and Johnson (1979) also show that higher rural labor supply leads to greater adoption of labor intensive rice varieties in Taiwan.

The participation of farmers in extension program significantly affects their crop productivity. Access to information about improved agricultural inputs is pertinent to farm families. The knowledge and advisory services about new agricultural inputs play great role in farmers' technology adoption behavior. This indicates that technology adoption and extension program have a direct relationship. Hence, we use extension service as instrumental variable. This instrument is directly correlated with our treatment indicators and uncorrelated with the outcome variables. The validity of the instrument is also tested using a simple falsification test following (Di Falco et al., 2011). It shows that extension service is exogenous to farm households, and hence it is valid and relevant.

The positively significant effect of extension program indicates that access to extension service is critical in promoting yield increasing agricultural production technologies. Alene and Coulibaly (2009) finding also shows doubling research investments in Sub Saharan Africa would reduce poverty by 9 percent, this would not be realized without more efficient extension, credit, and input supply system. Farmers cannot adopt new technologies without being aware of it (Diagne and Demont, 2007). Access to extension service therefore creates the platform for acquisition of relevant information that promotes technology adoption (Akudugu et al., 2012). Disseminating information through training programs increases farmer skills and awareness about new technologies and farm practices.

Livestock is one of the important economic factors in the rural farm family. The number of oxen farmers owned positively and significantly affect agricultural production. This implies that farmers that have more oxen have high rate of adoption of agricultural technologies. Availability of oxen during the main agricultural season (sowing and thrashing) help farmers to collect farm output on time. Due to agro-ecological conditions, productivity may also vary across regions. Taking into account such differences, we include regional dummy in the analysis. Using region four (Oromia region) as a reference, location dummy turns out to be significant, indicating that technology adoption affect all the surveyed regions crop productivity, yet the effect is lower in the other three regions than our reference region. This could be because in region four there is favorable agro-ecological environment for agricultural production. Our dataset also include more farm households from this region. Year dummy is also significant, indicating that agricultural productivity in the study areas increases over the years through improved technologies use.

The sample selection model result shown in Table 6 is comparable with the result found in the endogenous treatment effect model.

Table 6: Sample selection model estimation result

	HYV		Fertilizer		Multiple	
Value of production	Coeff.	Std. Err.	Coeff	Std. Err.	Coeff.	Std. Err.
Treatment indicator	15.281***	2.222	6.716***	0.863	5.860***	0.953
Gender of household head	-0.292	0.382	0.487	0.350	-0.380	0.427
Age of household head	0.046	0.051	-0.037	0.053	-0.028	0.059
Age square	-0.984	2.450	0.516	2.343	0.416	2.720
Educational level2	1.471***	0.462	-0.064	0.945	0.213	0.700
Educational level3	0.852**	0.435	-0.266	0.837	0.240	0.655
Educational level4	-0.184	0.458	0.218	0.745	0.133	0.588
Household size	-0.321***	0.069	-0.040	0.056	-0.014	0.075
Credit taken	-0.119	0.287	-0.171	0.276	-0.505	0.345
Off/Non-farm income	0.003	0.002	-0.002	0.002	-0.008	0.007
Farm size cultivated	2.331***	0.196	1.025***	0.379	1.284***	0.304
Quality of land2	0.319	0.327	-0.661**	0.298	0.771*	0.380
Quality of land3	-0.130	0.501	-1.063**	0.475	-0.291	0.564
Slope of land2	-0.509	0.379	-0.610**	0.360	-0.385	0.406
Slope of land3	-0.910	1.436	-0.885	1.369	-0.846	1.363
Labor use	0.007***	0.002	0.005***	0.004	0.004	0.003
Irrigation use	-1.701***	0.462	0.096	0.420	-1.173**	0.474
Soil conservation practice	0.500	0.313	0.656**	0.301	-0.735**	0.373
Number of livestock owned	0.037	0.041	-0.010	0.041	-0.006	0.052
Number of oxen owned	1.432***	0.179	0.737**	0.355	0.897***	0.300
Tigray	-2.580***	0.703	-0.189	0.767	-1.069	0.780

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Table 6 – continued

Amhara	1.390***	0.520	0.145	0.395	0.413	0.604
SNNPR	-6.405***	0.574	-2.819***	0.402	-3.949***	0.539
Year	0.928**	0.379	-2.744***	0.476	-1.874***	0.568
Age of household head	0.002	0.027	-0.002	0.023	-2.405	0.024
Educational level2	-0.431	1.283	0.903	1.043	0.547	1.099
Educational level3	-1.150	0.914	0.660	0.928	-0.237	0.874
Educational level4	0.279	0.956	-0.134	0.852	0.497	0.851
Labor use	0.003	0.004	0.002	0.005	0.002	0.005
Farm size cultivated	-0.556	0.436	0.958	0.416	1.099	0.450
Number of oxen owned	-0.179	0.305	0.534	0.365	-0.112	0.328
$L1$	-6.861***	1.189	-4.389***	0.835	-3.510***	0.796
$L0$	14.595***	1.873	2.220***	0.517	2.354***	0.637
Constant	-0.321	6.953	0.174	6.672	1.862	7.617
Number of obs		1150		1151		396
Prob > F		0.000		0.000		0.000
R-squared		0.545		0.534		0.674
Adj R-squared		0.532		0.520		0.644
Root MSE		4.365		4.174		2.886

***, ** and * indicates the values statistically significant at 1, 5 and 10 percent level.

Results from the matching methods are also fairly consistent. However, we reported higher value of production in the case of matching methods than in the other two model estimation results (see Table 7). This may be because of the conditional independence assumption for the matching method estimates without taking into account of the unobservable factors.

Table 7: Matching method estimation result

	Value of production					
Treatment indicator	PSM			NNM		
	Coeff.	Std.Err.	P-value	Coef.	Std. Err.	P-value
HYV						
ATET	1520.88	892.44	0.088			
ATE	781.73	411.83	0.058	727.32	388.09	0.061
Inorganic fertilizer						
ATET	4334.25	286.99	0.000			
ATE	3446.34	228.93	0.000	2179.87	212.77	0.000
HYV and fertilizer						
ATET	6188.37	748.02	0.000			
ATE	3499.42	385.60	0.000	2073.87	391.63	0.000

5.2 Household welfare impact of technology adoption

Controlling for household specific characteristics that determine the status of household wellbeing, as many literature on household welfare have pointed out, we estimate the impacts of technology adoption on welfare. The endogenous treatment effect model result shows that agricultural technology adoption positively affects welfare of households' in Ethiopia. The positive correlation we observe between technology adoption and welfare outcome may be attributed to the impact of HYVs and inorganic fertilizer. These technologies could directly affect farm output which translates into consumption at household level. This also implies that the opportunity for enhancing the role of adoption of agricultural technologies is larger that contributes to poverty reduction. Our result is consistent with existing studies. For instance, Mendola (2007) reported improved rice HYVs increase income of adopters and reduces the probability of falling into poverty in rural Bangladesh. Mulugeta and Hundie (2012) also found adoption of improved wheat technology in Ethiopia resulted in positive effect on household food consumption.

The model result shows that the average treatment effect on the treated households (ATET) is the same as the average treatment effect (ATE). This implies that the average predicted outcome for the treatment group is the same as the average predicted outcome for the whole population. Adoption of HYVs contributes to welfare of households in terms of spending on food and non-food items, an increase by 1.17 percent. The correlation coefficient between the first stage adoption regression and welfare outcome regression shows -0.89 and -0.15, respectively. This implies that there is strong relationship between agricultural technology adoption and farm households' well-being. The likelihood ratio test also shows statistically significant result, indicating that we can reject the null hypothesis of no correlation between technology adoption and welfare. Table 8 below shows the treatment effect model estimation result.

Table 8: Endogenous treatment effect estimation result

	HYV		Fertilizer		Multiple	
Rpc consumption Exp.	Coeff.	Std. Err.	Coeff	Std. Err.	Coeff.	Std. Err.
Treatment indicator	1.170***	0.047	0.259***	0.098	0.423***	0.123
Gender of household head	0.037	0.044	0.032	0.049	-0.004	0.057
Age of head	0.004	0.006	-0.000	0.006	0.006	0.007
Age square	0.141	0.295	0.248	0.334	-0.180	0.365
Educational level2	0.108	0.069	0.052	0.058	0.045	0.075
Educational level3	0.066	0.062	0.115**	0.053	0.080	0.062
Educational level4	0.016	0.063	0.075	0.054	0.067	0.059
Household size	-0.090***	0.007	-0.104***	0.008	-0.064***	0.009
Credit taken	0.020	0.034	0.081**	0.039	-0.060	0.046
Off/Non-farm income	0.000	0.000	0.000	0.000	0.000	0.000
Farm size cultivated	0.062**	0.026	0.025	0.023	0.036	0.031
Quality of land2	-0.060*	0.036	-0.069 **	0.041	-0.072	0.049
Quality of land3	-0.033	0.059	-0.007	0.065	-0.097	0.073
Labor use	-0.000	0.000	0.000	0.000	0.000	0.000
Irrigation use	-0.019	0.049	-0.027	0.058	0.038	0.061
Number of TLU owned	0.010**	0.004	0.014***	0.005	0.017**	0.007
Number of oxen owned	0.058**	0.024	0.048**	0.023	-0.001	0.030
Tigray	-0.289***	0.084	-0.231**	0.096	-0.210**	0.094
Amahra	-0.163***	0.043	-0.181***	0.050	-0.042	0.064
SNNPR	-0.448***	0.048	-0.409***	0.055	-0.315***	0.065

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Year	0.403***	0.040	0.366***	0.049	0.338***	0.059
Constant	0.088	0.839	0.021	0.949	1.163	1.027
Treatment indicator						
Expenditure for inputs	0.016***	0.004	0.064***	0.011	0.069***	0.013
Extension program	0.289***	0.062	-0.478***	0.089	0.034	0.135
Age of head	-0.008	0.002	-0.000	0.003	-0.008	0.005
Educational level2	-0.216	0.135	0.135	0.147	-0.147	0.237
Educational level3	0.067	0.110	0.204	0.128	0.247	0.186
Educational level4	0.052	0.111	-0.098	0.126	-0.109	0.184
Labor use	-0.000	0.000	-0.002	0.000	-0.001	0.001
Farm size cultivated	-0.085	0.046	0.103	0.057	-0.032	0.094
Number of oxen owned	-0.018	0.039	0.190	0.049	0.171	0.076
Constants	-0.374	0.171	0.630	0.190	0.079	0.295
athrho	-1.467	0.065	-0.151	0.087	-0.318	0.193
lnsigma	-0.329	0.024	-0.503	0.021	-0.898	0.048
rho	-0.899	0.012	-0.150	0.085	-0.308	0.175
sigma	0.719	0.017	0.604	0.013	0.407	0.019
lambda	-0.647	0.022	-0.090	0.052	-0.125	0.075
Estimator: ml						
Log likelihood		-1482.4047		-1591.33		-446.06
Number of obs		1151		1159		400
Prob > chi2		0.000		0.000		0.000

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Table 8 – continued

LR test (rho=0):	chi2(1)=184.5	chi2(1)=2.0	chi2(1)=2.3

Looking at formal years of schooling, education significantly affects farmers' adoption of improved technologies which ultimately resulted in improving household welfare. This indicating that education is positively correlated with farm households' livelihood activity. Education is a human asset that increases producers' knowledge. Farm households using family labor is common for agricultural activity in rural areas. However, a negatively significant effect of large household size on welfare outcome indicates that, the average land holding size and households size are not proportional (see Table 1). Hence, large family size negatively affect consumption. Similarly, Bezu et al. (2014) reported that once the labor contribution of the households is controlled for, large family size has negative effect on wellbeing of households. This indicates that there is surplus labor in rural areas, intervention on non-farm economic activity may consume the surplus labor. It also diversifies household income and reduces poverty in rural areas. Household wealth related variables such as land holding size either own or rented land significantly affects farmers improved input use. Farmers who have more land size can set aside larger areas for modern technologies, and hence will have better own consumption.

Access to technical advice through extension program reduces the uncertainty on technology performance. Extension service significantly influences the decision to adopt improved technologies. The positively significant effect of extension service indicates that, increasing farmers' knowledge in the adoption and management of new inputs improves agricultural productivity that ultimately affect food consumption at household level. However, with imperfect knowledge about new agricultural technologies, farmers may watch out their neighboring experience (Foster and Rosenzweig, 1995). But, one farmer's profitable technique could be unprofitable for another one and in this circumstance acquiring knowledge from extension worker improves the existing knowledge of farmers. Once farmers are aware of the intrinsic benefit of yield increasing technologies, the adoption may increase. Expenditure for HYVs and inorganic fertilizer also shows up as positive and significant. Our expectation was that the cost of improved inputs may negatively affect adoption. Perhaps once farmers are aware of improved inputs potential, they may invest in yield-increasing technologies.

Access to credit in terms of cash and/or in-kind positively affect farmers technology adoption decision and welfare of households. Providing credit access is a public program to support rural smallholder farmers. This indicates that credit facility tackles the financial constraint of smallholders during the pick period of agricultural time. Modern agricultural technologies are expensive that farmers face difficult, especially in the rural area where poverty is endemic to be able to acquire and utilize without assistance in the form of affordable credit access and financial services (Benin et al., 2009).

Classifying farmers cultivated land into fertile, less-fertile, and non-fertile land, the causal effect of technology adoption on household welfare is affected by the type of land. Farmers who practice on fertile and less-fertile land experience significantly different affects on their household's welfare. This indicates that since the livelihood of rural households depends on agriculture, increasing the productivity of land through modern agricultural technologies and practicing soil conservation measures increase agricultural production that reduce poverty among rural farm families. This is because land degradation in the form of nutrient depletion is a treat to food security, farmers conserving the fertility of soil enable agricultural production to be sustainable (Kassie and Holden, 2006).

Possession of livestock is an asset to farm families. On the one hand, it is one of the means of income diversification mechanism, on the other hand, it is the main input for agricultural activities such as sowing and threshing. The total number of livestock and oxen households owned measured in tropical livestock unit is positively correlated with welfare of households. This implies that the number of livestock farmers owned helps them through its influence on income either selling the live animals or using as income generating mechanism. Studies indicate that farm households working in off-farm wage employment are those having more transport animals (Woldehanna and Oskam, 2001). Holden et al. (2004) also show that livestock wealth is a better indicator of household wealth and wealth differentiation. As we explained earlier, location and time effects in the adoption of improved technologies resulted in significant impacts on welfare outcome as well. This indicates that the use of yield increasing agricultural technologies enhances welfare of rural households across the regions and through time.

The estimation result of sample selection model shown in Table 9 and matching techniques in Table 10 are comparable with the result found in the endogenous treatment effect model. Exceptionally, we are unable to see the effect in the case of combined adoption.

Table 9: Sample selection model estimation result

	HYV		Fertilizer		Multiple	
Real Pc consumption Exp.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Treatment indicator	1.106***	0.307	0.232*	0.126	0.191	0.131
Gender of household head	-0.024	0.052	0.040	0.050	0.023	0.058
Age of household head	0.003	0.007	-0.006	0.007	0.001	0.008
Age square	0.195	0.337	0.334	0.340	-0.069	0.373
Educational level2	0.098	0.063	0.003	0.137	0.050	0.096
Educational level3	0.107*	0.059	0.161	0.121	0.112	0.089
Educational level4	-0.027	0.063	0.045	0.107	-0.005	0.080
Household size	-0.122***	0.009	-0.106***	0.008	-0.071***	0.010
Credit taken	0.077**	0.039	0.075*	0.040	-0.052	0.047
Off/Non-farm income	0.000	0.000	0.000	0.000	0.002**	0.000
Farm size cultivated	0.037	0.026	-0.026	0.054	-0.087**	0.041
Quality of land2	-0.000	0.044	-0.069 *	0.042	-0.049	0.050
Quality of land3	0.039	0.068	-0.027	0.067	-0.121	0.075
Labor use	-0.000	0.000	0.000	0.000	0.000*	0.000
Irrigation use	-0.144**	0.063	-0.001	0.061	-0.001	0.064
Number of livestock owned	0.014***	0.005	0.012**	0.005	0.018***	0.007
Number of oxen owned	0.047**	0.024	0.086*	0.051	0.051	0.041
Tigray	-0.274***	0.094	-0.139	0.110	-0.177*	0.106
Amhara	-0.037	0.071	-0.132**	0.057	-0.034	0.082
SNNPR	-0.615***	0.079	-0.415***	0.057	-0.248***	0.070

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Table 9 – continued

Year	0.488***	0.051	0.298***	0.071	0.384***	0.076
Age of household head	0.003	0.003	0.005	0.003	0.005	0.003
Educational level2	-0.083	0.176	0.049	0.151	-0.046	0.150
Educational level3	0.108	0.126	-0.067	0.134	0.042	0.119
Educational level4	0.166	0.131	-0.008	0.123	0.160	0.115
Labor use	-0.000	0.000	-0.001	0.000	-0.001	0.000
Farm size cultivated	0.119	0.060	0.067	0.060	0.280	0.061
Number of oxen owned	-0.027	0.042	-0.052	0.053	-0.088	0.044
$L1$	-0.471***	0.164	-0.210*	0.123	0.009	0.109
$L0$	0.751***	0.259	0.020	0.075	-0.029	0.087
Constant	0.033	0.958	0.075	0.968	1.056	1.046
Number of obs		1151		1148		396
Prob > F		0.000		0.000		0.000
R-squared		0.290		0.279		0.371
Adj R-squared		0.271		0.260		0.327

Table 10: Matching method estimation result

	Welfare					
Treatment indicator	PSM			NNM		
	Coeff.	Std.Err.	P-value	Coef.	Std. Err.	P-value
Improved seed						
ATET	8.299	4.899	0.090			
ATE	-0.455	4.657	0.922	8.455	4.764	0.076
Inorganic fertilizer						
ATET	21.80	3.690	0.000			
ATE	25.55	4.204	0.000	20.29	3.934	0.000
Improved seed and inorganic fertilizer						
ATET	18.30	4.861	0.000			
ATE	10.88	6.064	0.073	13.22	6.253	0.034

6 Conclusion

This research evaluates the impact of HYVs and inorganic fertilizer on crop productivity and households welfare. Since farm households are not randomly assigned to the technologies, there is self-selection into treatment (technology adoption). Endogenous treatment effect model is employed in order to account for the selection bias in adoption decision. The main result shows that modern agricultural technology adoption positively contributes to smallholders crop productivity and welfare of rural households in Ethiopia.

The factors that influence farmers adoption decision include educational level of the household head, farm size, labor use, the type of cultivated land in terms of fertility, slope of the land, irrigation use, participation in extension program, expenditure on modern inputs and access to credit. Therefore, relaxing credit constraints to adoption of technologies, quality of extension service and other institutional factors are key determinants positively affecting adoption. Rural education through various means, information, and trainings are major factors affecting farmers' economic decision. Influencing the intrinsic behavior of farmers through knowledge creation, perception and attitude towards improved inputs helps farmers to learn about new technologies. To boost productivity and improve welfare of rural households, governmental and non-governmental organizations should promote wider scale use of agricultural technologies.

The results in this paper offer evidence to the potential impact of agricultural technologies use on crop productivity and welfare of households when they have secured access to improved HYVs and inorganic fertilizer. This is because the result indicates that most smallholder farmers in rural area used local seed for cereal crop production and local seed remains the dominant system. The policy implication derived from the results includes the following. First, policy priority on investment in research and development of improved crop varieties adapted to local agro-ecological condition is needed to fulfill farmers' demand for improved seed. Second, to increase the opportunity of accessing HYVs and inorganic fertilizer in rural areas, participation of private sector involvement in improved agricultural technologies supply system through government quality assurance should be the government strategy to reduce the low adoption rate. Third, giving policy priority for extension service in developing technical expertise and assign at local need to increase farmers' knowledge about input potential, provide technical advice for the management and application of the new technologies at the recommended rate. The results are in agreement with other research finding on impact of technology adoption, (Akudugu et al., 2012; Simtowe et al., 2012; Kijima et al., 2008; Hossain et al., 2003; De Janvry and Sadoulet, 2002a).

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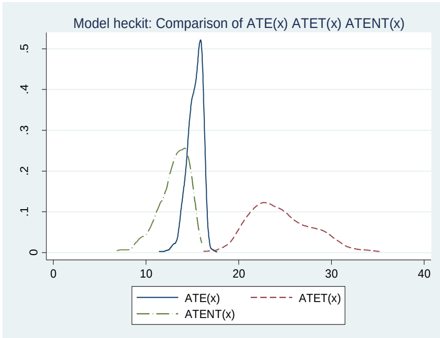
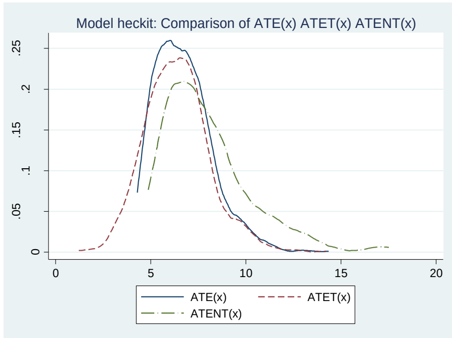
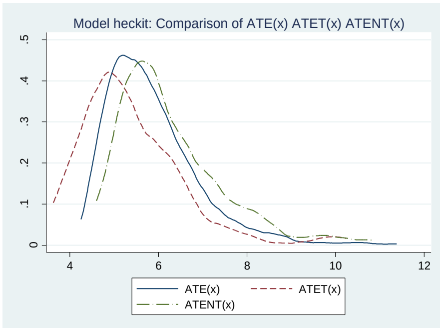
Figure 1 Distribution of ATE(x), ATET(x) and ATENT(x) of improved technologies



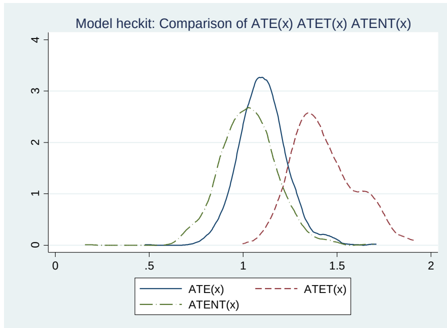
(a) HYVs



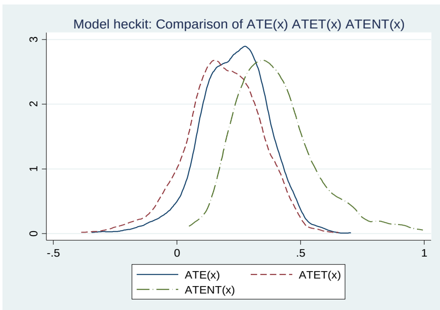
(b) Chemical fertilizer



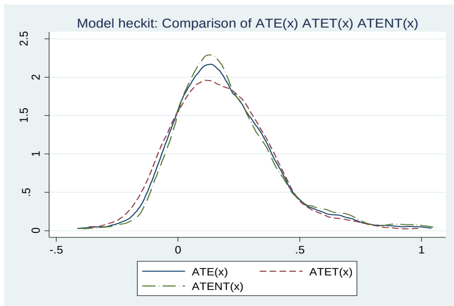
(c) Combined adoption



(d) HYVs



(e) Chemical fertilizer



(f) Combined adoption

Note: a, b, and c shows ATE(x), ATET(x), and ATENT(x) of HYVs and chemical fertilizer use on crop productivity, where as d, e and f shows welfare outcome.

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